Next Word Prediction Using LSTM's

In this example we will work on the following text

Project Gutenberg - Sherlock Holmes

Data Download link

https://statso.io/next-word-prediction-case-study/

Reference Text from NVIDIA - Learning Deep Learning

https://www.nvidia.com/en-in/training/books/

Primary Code reference

https://medium.com/@ilaslanduzgun/next-word-prediction-using-lstm-with-tensorflow-e2a8f63b613c

Other Reference Blogs

[1] https://www.analyticsvidhya.com/blog/2021/08/predict-the-next-word-of-your-text-using-long-short-term-memory-lstm/

[2]https://medium.com/geekculture/next-word-prediction-using-lstms-98a1edec8594

[3] https://www.geeksforgeeks.org/next-word-prediction-with-deep-learning-in-nlp/

[4] https://thecleverprogrammer.com/2020/07/20/next-word-prediction-model/#google_vignette

[5] https://github.com/abhi227070/Next-Word-Prediction-Using-LSTM

Section 1: Tutorial Note on Next Word Prediction

Ref [4]

- Identifying the most likely word to follow a given string of words is the basic goal of the Natural Language Processing (NLP) task of “next word prediction.”
- This predictive skill is essential in various applications, including text auto-completion, speech recognition, and machine translation.
- Deep learning approaches have transformed NLP by attaining remarkable success in various language-related tasks, such as next-word prediction.

1 a) Model Architecture

The model architecture for next-word prediction typically consists of the following components:

- **Embedding Layer:** The word embeddings, often referred to as distributed representations of words, are learned by the embedding layer. It captures semantic and contextual information by mapping every word in the lexicon to a dense vector representation. The model can be trained to change these embeddings as trainable parameters.

- **Recurrent Layers:** The recurrent layers, like LSTM or GRU, process the input word embeddings in sequential order and keep hidden states that record the sequential data. The model can learn the contextual connections between words and their placements in the sequence thanks to these layers.

- **Dense Layers:** One or more dense layers are then added after the recurrent layers to convert the learned features into the appropriate output format. When predicting the next word, the dense layers translate the hidden representations to a probability distribution across the vocabulary, indicating the likelihood that each word will be the following word.

1 b) Training and Optimization

The model is trained using a large corpus of text data, where the input sequences are paired with their corresponding target word. The training process involves optimizing the model’s parameters by minimizing a suitable loss function, such as categorical cross-entropy.

1 c) Inference and Prediction

- The model can be used to predict the next word once it has been trained.

- The trained model receives an input of a list of words, processes it through the learned architecture, and outputs a probability distribution across the vocabulary.

- The anticipated next word is then chosen as the one with the highest likelihood.

- Typically the predicted next word is augmented to the initial seed word sequence and fed again to get the 'next' word.

- The process is repeated till the desired length of output sequence is achieved

Section 2: Implementation Strategy A - Split into sentences at ".", "?", "!" and new line character

The key steps involved in this implementation are

- Import required libraries
- Read input file
- Tokenize text
-

Step 1 : Import libraries

In [3]:

```
import tensorflow as tf
import pickle
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Embedding, LSTM, Dense
from tensorflow.keras.preprocessing.text import Tokenizer
from tensorflow.keras.preprocessing.sequence import pad_sequences
import matplotlib.pyplot as plt
import numpy as np
import regex as re
```

Step 2: Read Input file

The below function `file_to_sentence_list()` is uded to read the input text, as explained below

Function Signature:

- The function accepts a file_path of type str and returns a list of sentences (list).

Parameters:

- file_path: The file path pointing to the text file that needs to be processed.

Return Value:

- Returns a list where each element is a line from the file, with surrounding spaces removed.

Error Handling:

- The try-except blocks are to catch and raise meaningful errors, including FileNotFoundError and general exceptions.

Splitting the input text into senetences

- `re.split()` function, which splits the text at any occurrence of `., ?, !`, or new lines `(\n)`.
- `\s*` ensures that any whitespace after the punctuation is ignored.
- The `\n+` handles multiple new lines together.

Filter Sentences:

- The list comprehension includes if sentence.strip(), which ensures empty strings (from extra spaces or blank lines) are filtered out.
- If a sentence has one word only it is also filtered out

In [5]:

```
def file_to_sentence_list(file_path: str) -> list:
    """
    Reads a text file from the given file path and returns a list of senten
    Each line in the file is treated as a sentence and stripped of leading/

    Parameters:
    ----------
    file_path : str
        The path to the text file to be read.

    Returns:
    -------
    list
        A list of sentences where each element represents a line from the fi
        and trailing whitespace removed.

    """
    try:
        with open(file_path, 'r', encoding='utf-8') as file:
            text = file.read()

        # Use regular expressions to split based on ., ?, !, and new lines
        sentences = re.split(r'[.!?]\s*|\n+', text)

        # Strip leading and trailing whitespace from each sentence and filte
        sentences = [sentence.strip() for sentence in sentences if sentence

        # filter out empty sentences having one word only
        sentences = [sentence for sentence in sentences if len(sentence.spli

        return sentences
    except FileNotFoundError as e:
        print(f"Error: File not found - {file_path}")
        raise e
    except Exception as e:
        print(f"An error occurred while reading the file: {e}")
        raise e
```

In [6]:

```
# define file path
file_path = 'sherlock_holmes.txt'

# call function to read data
text_data = file_to_sentence_list(file_path)

# check Sentence count
print("Number of Sentences read is = ",len(text_data))

# print the first sentence
print("First Sentence --> ",  text_data[0])

print("Second Sentence --> ", text_data[1])

# print the second sentence
print("Third Sentence -->",   text_data[2])
```

```
Number of Sentences read is =  12914
First Sentence -->  A SCANDAL IN BOHEMIA
Second Sentence -->  To Sherlock Holmes she is always _the_ woman
Third Sentence --> I have seldom heard him
```

Step 3 Tokenise text data

Key substeps are

- Fit Tokenizer on text data

- Create Input Sequences
- Convert target data to one hot encoding

Step 3a : Fit Tokenizer

In [7]:

```
# Tokenize the text data
tokenizer = Tokenizer()

# fit
tokenizer.fit_on_texts(text_data)


#assign length of word index
total_words = len(tokenizer.word_index) + 1


# Count of Unique Words
print(" Total count of unique words : ", total_words)
```

```
 Total count of unique words :  8783
```

In [8]:

```
# check the tokens  first 10 only
cnt = 0
for key, value in tokenizer.word_index.items():

    if cnt > 9:
        break
    print(f"Key: {key}, Value: {value}")
    cnt = cnt + 1
```

```
Key: the, Value: 1
Key: and, Value: 2
Key: to, Value: 3
Key: of, Value: 4
Key: a, Value: 5
Key: i, Value: 6
Key: in, Value: 7
Key: that, Value: 8
Key: it, Value: 9
Key: he, Value: 10
```

Step 3b : Create Input Sequence using n - grams

The code is explained below in detail

1. `input_sequences = []`

- Purpose: This creates an empty list input_sequences to store sequences of tokens that will be generated in the subsequent steps.
- This list will eventually hold all the n-gram sequences extracted from the text_data.

2. `for line in text_data`:

- Purpose: This loops through each line in text_data.
- Here, text_data is a list of sentences or lines, where each line represents a string (e.g., a sentence from some text).

- This prepares each sentence for tokenization.

3. `token_list = tokenizer.texts_to_sequences([line])[0]`

- Purpose: Tokenizes the current line (sentence) into a sequence of numbers (tokens).

Explanation:

- tokenizer.texts_to_sequences([line]): This method converts the given text (in this case, a single sentence line) into a sequence of integers, where each integer represents a unique token (word) in the sentence.

- The texts_to_sequences method returns a list of sequences (because it accepts multiple texts as input), but since we only passed one sentence ([line]), we extract the first and only sequence using [0].

- Now, token_list contains the list of tokens for that line.

4. `for i in range(1, len(token_list))`:

- Purpose: This loops over the tokenized list of words to create "n-grams".

Explanation:

- This loop runs from i = 1 to the length of token_list minus 1.

- The purpose here is to generate n-grams from the token list.

- The i+1 ensures that each loop iteration selects an increasingly larger portion of the token list (starting from 2 tokens, up to the full sentence).

5. `n_gram_sequence = token_list[:i+1]`

- Purpose: Generates an n-gram sequence.

Explanation:

- The `token_list[:i+1]` slices the tokenized sentence from the beginning (index 0) to the (i+1)th token.

For example, if `token_list = [3, 15, 7, 29]`:

- At i = 1, n_gram_sequence will be [3, 15].
- At i = 2, n_gram_sequence will be [3, 15, 7].
- At i = 3, n_gram_sequence will be [3, 15, 7, 29].

6. input_sequences.append(n_gram_sequence)

- Purpose: Adds the generated n-gram sequence to the input_sequences list.

Explanation:

- With each iteration of the inner loop, the new n-gram is appended to the input_sequences list.

- This list now contains n-gram sequences of increasing length, which can later be used for training purposes (e.g., for a language model).

Create Input Sequence

In [9]:
```
# Create Input Sequences
input_sequences = []
#split the sentence from '\n'
for line in text_data:
    #get tokens
    token_list = tokenizer.texts_to_sequences([line])[0]
    for i in range(1, len(token_list)):
        n_gram_sequence = token_list[:i+1]
        input_sequences.append(n_gram_sequence)
```

Check 1st 10 Input Sequences

In [10]:
```
# check 1st ten input sequences
for i in range(0, 10):
    print(input_sequences[i])
```

```
[5, 925]
[5, 925, 7]
[5, 925, 7, 1065]
[3, 133]
[3, 133, 38]
[3, 133, 38, 37]
[3, 133, 38, 37, 14]
[3, 133, 38, 37, 14, 226]
[3, 133, 38, 37, 14, 226, 1]
[3, 133, 38, 37, 14, 226, 1, 227]
```

Check The sentence for input sequence 2

In [11]:
```
sentence_token = input_sequences[2] # [5, 925, 7, 1065]

sentence = []
for token in sentence_token:
    sentence.append(list((tokenizer.word_index).keys())[list((tokenizer.wor
print(sentence)
```

```
['a', 'scandal', 'in', 'bohemia']
```

Step 3c : Pad Sequences

- Determine max length input sequence
- Pad all input sequences with pre zeros to match length of max sequence

How Padding Helps in NLP Tasks:

- Consistent Input Size: Most deep learning models (like LSTMs) expect inputs of the same size. Padding ensures that each sequence has the same number of tokens.
- Batch Processing: When training on multiple sequences at once (batching), padding ensures that sequences of varying lengths can be processed together as matrices with uniform dimensions.

- Pre-padding (padding='pre'): This is common for models that care more about the recent tokens. The zeros at the start act as placeholders and do not affect learning, allowing the model to focus on the last tokens in the sequence.

In [12]:

```
# Pad sequences and split into predictors and label
max_sequence_len = max([len(seq) for seq in input_sequences])
input_sequences = np.array(pad_sequences(
    input_sequences, maxlen=max_sequence_len, padding='pre'))
```

Step 3d : Create X and y Data

- Choose the last token for every sequence as Y data
- Choose all tokens upto the last token as X data for every sequence
- Convert Y value to One hot Encoded values

In [13]:

```
X, y = input_sequences[:, :-1], input_sequences[:, -1]

# Convert target data to one-hot encoding
y = tf.keras.utils.to_categorical(y, num_classes=total_words)
```

Step 4 Define the model

- The input sequences are mapped to dense vectors of fixed size in the first layer, which is an embedding layer.

- It requires three arguments: input_length (the length of the input sequences less one because we are predicting the next word), 10 (the dimensionality of the embedding space), and total_words (the total number of unique words in the vocabulary).

- An LSTM (Long Short-Term Memory) layer with 128 units makes up the second layer.

- A Dense layer with total_words units and softmax activation make up the third layer. The output probabilities for each word in the vocabulary are generated by this layer.

- The categorical cross-entropy loss function used in the model is appropriate for multi-class classification applications.

- Adam is the chosen optimizer, and accuracy is the evaluation metric.

In [ ]:

```
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Embedding, LSTM, Dense
from tensorflow.keras.preprocessing.sequence import pad_sequences
import tensorflow as tf

# Ensure that `total_words` and `max_sequence_len` are defined
# total_words should be the size of your vocabulary
# max_sequence_len should be the length of the longest sequence

# Define the model
model = Sequential()

# Embedding layer
```

```
model.add(Embedding(input_dim=total_words, output_dim=10, input_length=max_
#model.add(Embedding(input_dim=total_words, output_dim=10))

# LSTM layer with 128 units
model.add(LSTM(128))

# Output layer - Dense with softmax activation for multiclass classificatio
model.add(Dense(total_words, activation='softmax'))

# Compile the model
model.compile(loss='categorical_crossentropy', optimizer='adam', metrics=['a
```

Step 5 Train the Model

- Note we are training for 100 Epochs

In [ ]:

```
# Train the model
history = model.fit(X, y, epochs=100,validation_split=0.05, verbose=1).histo
```

Step 6 : Print model Summary

- Note once molde is trained the structure will be built
- It may not be built after compile step

In [ ]:

```
# Print model summary to verify the structure
print(model.summary())
```

Step 7 : Save Model object post training completion

In [ ]:

```
# Save the model after training
model.save('lstm_model.h5')
print("Model saved as lstm_model.h5")
```

Step 8 : Load from saved model object

In [ ]:

```
# load saved model
from tensorflow.keras.models import load_model
loaded_model = load_model('lstm_model.h5')
```

Step 9: Save the model history

In [ ]:

```
pickle.dump(history, open("history.p", "wb"))
```

Step 10 : Load history from saved pickle file

In [ ]:

```
history = pickle.load(open("history.p", "rb"))
```

Step 11: Evaluating the model

- Evaluate Model Accuracy vs Number of Epochs
- Evaluate Model Loss Vs Number of Epochs

Step 11 a : Evaluate Model Accuracy vs Number of Epochs

In [ ]:

```
plt.plot(history['accuracy'])
plt.plot(history['val_accuracy'])
plt.title('model accuracy')
plt.ylabel('accuracy')
plt.xlabel('epoch')
plt.legend(['train', 'test'], loc='upper left')
```

Step 11 b : Evaluate Model Loss Vs Number of Epochs

In [ ]:

```
plt.plot(history['loss'])
plt.plot(history['val_loss'])
plt.title('model loss')
plt.ylabel('loss')
plt.xlabel('epoch')
plt.legend(['train', 'test'], loc='upper left')
```

Section 4: Implementation Strategy B - Split into sentences by ONLY new line character

Modified function to split sentence by new line character only

In [ ]:

```
def file_to_sentence_list_2(file_path: str) -> list:
    """
    Reads a text file from the given file path and returns a list of sentenc
    
    Each line in the file is treated as a sentence and stripped of leading/t
    
    Parameters:
    ----------
    file_path : str
        The path to the text file to be read.
    
    Returns:
    --------
    list
        A list of sentences where each element represents a line from the fi
        and trailing whitespace removed.
    
    """
    try:
        with open(file_path, 'r', encoding='utf-8') as file:
            text = file.read()
        
        # Use regular expressions to split based on ., ?, !, and new lines
        
        sentences = text.split('\n')
        
        # Strip leading and trailing whitespace from each sentence and filte
        sentences = [sentence.strip() for sentence in sentences if sentence 
        
        # filter out empty sentences having one word only
        sentences = [sentence for sentence in sentences if len(sentence.spli
        
        return sentences
    except FileNotFoundError as e:
        print(f"Error: File not found - {file_path}")
        raise e
    except Exception as e:
        print(f"An error occurred while reading the file: {e}")
        raise e
```

In [ ]:

```
# define file path
file_path = 'sherlock_holmes.txt'

# call function to read data
text_data = file_to_sentence_list_2(file_path)

# check Sentence count
print("Number of Sentences read is = ",len(text_data))

# print the first sentence
print("First Sentence --> ",  text_data[0])

print("Second Sentence --> ", text_data[1])

# print the second sentence
print("Third Sentence -->",   text_data[2])
```

Tokenize the text data after new split strategy

In [ ]:

```
# Tokenize the text data
tokenizer = Tokenizer()

# fit
tokenizer.fit_on_texts(text_data)


#assign length of word index
total_words = len(tokenizer.word_index) + 1


# Count of Unique Words
print(" Total count of unique words : ", total_words)
```

Create N gram based input sequence

In [ ]:

```
# Create Input Sequences
input_sequences = []
#split the sentence from '\n'
for line in text_data:
    #get tokens
    token_list = tokenizer.texts_to_sequences([line])[0]
    for i in range(1, len(token_list)):
        n_gram_sequence = token_list[:i+1]
        input_sequences.append(n_gram_sequence)
```

Pad Sequences for uniform length

In [ ]:

```
# Pad sequences and split into predictors and label
max_sequence_len = max([len(seq) for seq in input_sequences])
input_sequences = np.array(pad_sequences(
    input_sequences, maxlen=max_sequence_len, padding='pre'))
```

Create X and Y Data, hot encode Y data

In [ ]:
```
X, y = input_sequences[:, :-1], input_sequences[:, -1]

# Convert target data to one-hot encoding
y = tf.keras.utils.to_categorical(y, num_classes=total_words)
```

Define the second model

In [ ]:
```
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Embedding, LSTM, Dense
from tensorflow.keras.preprocessing.sequence import pad_sequences
import tensorflow as tf

# Ensure that `total_words` and `max_sequence_len` are defined
# total_words should be the size of your vocabulary
# max_sequence_len should be the length of the longest sequence

# Define the model
model2 = Sequential()

# Embedding layer
model2.add(Embedding(input_dim=total_words, output_dim=10, input_length=max_
#model.add(Embedding(input_dim=total_words, output_dim=10))

# LSTM layer with 128 units
model2.add(LSTM(128))

# Output layer - Dense with softmax activation for multiclass classificatio
model2.add(Dense(total_words, activation='softmax'))

# Compile the model
model2.compile(loss='categorical_crossentropy', optimizer='adam', metrics=[
```

Train the 2nd model

In [ ]:
```
# Train the model
history = model2.fit(X, y, epochs=100,validation_split=0.05, verbose=1).his
```

Save Model after training

In [ ]:
```
# Save the model after training
model2.save('lstm_model2.h5')
print("Model saved as lstm_model2.h5")
```

Load Saved model 2

In [ ]:
```
# load saved model
from tensorflow.keras.models import load_model
loaded_model2 = load_model('lstm_model2.h5')
```

Save History for model 2

In [ ]:
```
pickle.dump(history, open("history2.p", "wb"))
```

Load History for model 2

In [ ]:
```
history2 = pickle.load(open("history2.p", "rb"))
```

Plot History - Accuracy vs Epochs for model 2

In [ ]:
```
plt.plot(history2['accuracy'])
plt.plot(history2['val_accuracy'])
plt.title('model accuracy')
plt.ylabel('accuracy')
plt.xlabel('epoch')
plt.legend(['train', 'test'], loc='upper left')
```

Plot Loss Vs Epochs for model 2

In [ ]:
```
plt.plot(history2['loss'])
plt.plot(history2['val_loss'])
plt.title('model loss')
plt.ylabel('loss')
plt.xlabel('epoch')
plt.legend(['train', 'test'], loc='upper left')
```

Section 5: Implementation Strategy C - Split into sentences by ONLY new line character and Increase LSTM Layer nodes to 150

Define the 3rd model

In [14]:
```
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Embedding, LSTM, Dense
from tensorflow.keras.preprocessing.sequence import pad_sequences
import tensorflow as tf

# Ensure that `total_words` and `max_sequence_len` are defined
# total_words should be the size of your vocabulary
# max_sequence_len should be the length of the longest sequence

# Define the model
model3 = Sequential()

# Embedding layer
model3.add(Embedding(input_dim=total_words, output_dim=10, input_length=max_
#model.add(Embedding(input_dim=total_words, output_dim=10))

# LSTM layer with 150 units
model3.add(LSTM(150))

# Output layer - Dense with softmax activation for multiclass classificatio
model3.add(Dense(total_words, activation='softmax'))

# Compile the model
model3.compile(loss='categorical_crossentropy', optimizer='adam', metrics=[
/Users/anishroychowdhury/anaconda3/envs/LLM/lib/python3.10/site-packages/ke
ras/src/layers/core/embedding.py:90: UserWarning: Argument `input_length` i
s deprecated. Just remove it.
  warnings.warn(
```

Train the 3rd model

In [15]:

```
# Train the model
history = model3.fit(X, y, epochs=100,validation_split=0.05, verbose=1).his
```

```
Epoch 1/100
2818/2818 ━━━━━━━━━━━━━━━━━━━━ 46s 16ms/step - accuracy: 0.0566 - loss: 6.7
142 - val_accuracy: 0.0737 - val_loss: 7.4050
Epoch 2/100
2818/2818 ━━━━━━━━━━━━━━━━━━━━ 48s 17ms/step - accuracy: 0.0826 - loss: 5.9
383 - val_accuracy: 0.0965 - val_loss: 7.3540
Epoch 3/100
2818/2818 ━━━━━━━━━━━━━━━━━━━━ 50s 18ms/step - accuracy: 0.1175 - loss: 5.5
049 - val_accuracy: 0.1003 - val_loss: 7.5734
Epoch 4/100
2818/2818 ━━━━━━━━━━━━━━━━━━━━ 50s 18ms/step - accuracy: 0.1385 - loss: 5.1
925 - val_accuracy: 0.1123 - val_loss: 7.7089
Epoch 5/100
2818/2818 ━━━━━━━━━━━━━━━━━━━━ 47s 17ms/step - accuracy: 0.1516 - loss: 4.9
280 - val_accuracy: 0.1157 - val_loss: 7.8519
Epoch 6/100
2818/2818 ━━━━━━━━━━━━━━━━━━━━ 47s 17ms/step - accuracy: 0.1601 - loss: 4.7
112 - val_accuracy: 0.1176 - val_loss: 7.9306
Epoch 7/100
2818/2818 ━━━━━━━━━━━━━━━━━━━━ 47s 17ms/step - accuracy: 0.1674 - loss: 4.5
195 - val_accuracy: 0.1121 - val_loss: 8.0930
Epoch 8/100
2818/2818 ━━━━━━━━━━━━━━━━━━━━ 47s 17ms/step - accuracy: 0.1809 - loss: 4.3
286 - val_accuracy: 0.1169 - val_loss: 8.3257
Epoch 9/100
2818/2818 ━━━━━━━━━━━━━━━━━━━━ 49s 17ms/step - accuracy: 0.1946 - loss: 4.1
487 - val_accuracy: 0.1157 - val_loss: 8.5017
Epoch 10/100
2818/2818 ━━━━━━━━━━━━━━━━━━━━ 45s 16ms/step - accuracy: 0.2120 - loss: 3.9
755 - val_accuracy: 0.1106 - val_loss: 8.6610
Epoch 11/100
2818/2818 ━━━━━━━━━━━━━━━━━━━━ 44s 16ms/step - accuracy: 0.2327 - loss: 3.8
243 - val_accuracy: 0.1089 - val_loss: 8.7769
Epoch 12/100
2818/2818 ━━━━━━━━━━━━━━━━━━━━ 43s 15ms/step - accuracy: 0.2493 - loss: 3.6
703 - val_accuracy: 0.1096 - val_loss: 8.8822
Epoch 13/100
2818/2818 ━━━━━━━━━━━━━━━━━━━━ 44s 15ms/step - accuracy: 0.2675 - loss: 3.5
397 - val_accuracy: 0.0995 - val_loss: 9.0518
Epoch 14/100
2818/2818 ━━━━━━━━━━━━━━━━━━━━ 42s 15ms/step - accuracy: 0.2865 - loss: 3.4
217 - val_accuracy: 0.1026 - val_loss: 9.1364
Epoch 15/100
2818/2818 ━━━━━━━━━━━━━━━━━━━━ 43s 15ms/step - accuracy: 0.3039 - loss: 3.2
914 - val_accuracy: 0.1035 - val_loss: 9.2676
Epoch 16/100
2818/2818 ━━━━━━━━━━━━━━━━━━━━ 44s 15ms/step - accuracy: 0.3231 - loss: 3.1
903 - val_accuracy: 0.0982 - val_loss: 9.3985
Epoch 17/100
2818/2818 ━━━━━━━━━━━━━━━━━━━━ 41s 14ms/step - accuracy: 0.3373 - loss: 3.1
029 - val_accuracy: 0.1022 - val_loss: 9.5124
Epoch 18/100
2818/2818 ━━━━━━━━━━━━━━━━━━━━ 44s 16ms/step - accuracy: 0.3543 - loss: 3.0
058 - val_accuracy: 0.1005 - val_loss: 9.6241
Epoch 19/100
2818/2818 ━━━━━━━━━━━━━━━━━━━━ 45s 16ms/step - accuracy: 0.3686 - loss: 2.9
361 - val_accuracy: 0.1001 - val_loss: 9.6969
Epoch 20/100
2818/2818 ━━━━━━━━━━━━━━━━━━━━ 44s 16ms/step - accuracy: 0.3802 - loss: 2.8
498 - val_accuracy: 0.0961 - val_loss: 9.7978
Epoch 21/100
2818/2818 ━━━━━━━━━━━━━━━━━━━━ 43s 15ms/step - accuracy: 0.3944 - loss: 2.7
838 - val_accuracy: 0.0961 - val_loss: 9.9494
Epoch 22/100
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2818/2818 ━━━━━━━━━━━━━━━━━━━━ 45s 16ms/step - accuracy: 0.4106 - loss: 2.7
029 - val_accuracy: 0.0948 - val_loss: 10.0538
Epoch 23/100
2818/2818 ━━━━━━━━━━━━━━━━━━━━ 44s 16ms/step - accuracy: 0.4197 - loss: 2.6
486 - val_accuracy: 0.0950 - val_loss: 10.0687
Epoch 24/100
2818/2818 ━━━━━━━━━━━━━━━━━━━━ 43s 15ms/step - accuracy: 0.4303 - loss: 2.5
735 - val_accuracy: 0.0948 - val_loss: 10.1817
Epoch 25/100
2818/2818 ━━━━━━━━━━━━━━━━━━━━ 45s 16ms/step - accuracy: 0.4395 - loss: 2.5
340 - val_accuracy: 0.0940 - val_loss: 10.2892
Epoch 26/100
2818/2818 ━━━━━━━━━━━━━━━━━━━━ 45s 16ms/step - accuracy: 0.4525 - loss: 2.4
721 - val_accuracy: 0.0933 - val_loss: 10.3822
Epoch 27/100
2818/2818 ━━━━━━━━━━━━━━━━━━━━ 46s 16ms/step - accuracy: 0.4605 - loss: 2.4
230 - val_accuracy: 0.0879 - val_loss: 10.4814
Epoch 28/100
2818/2818 ━━━━━━━━━━━━━━━━━━━━ 45s 16ms/step - accuracy: 0.4669 - loss: 2.3
951 - val_accuracy: 0.0923 - val_loss: 10.5491
Epoch 29/100
2818/2818 ━━━━━━━━━━━━━━━━━━━━ 44s 16ms/step - accuracy: 0.4786 - loss: 2.3
404 - val_accuracy: 0.0944 - val_loss: 10.5868
Epoch 30/100
2818/2818 ━━━━━━━━━━━━━━━━━━━━ 46s 16ms/step - accuracy: 0.4817 - loss: 2.3
145 - val_accuracy: 0.0877 - val_loss: 10.6841
Epoch 31/100
2818/2818 ━━━━━━━━━━━━━━━━━━━━ 44s 16ms/step - accuracy: 0.4851 - loss: 2.2
881 - val_accuracy: 0.0917 - val_loss: 10.7832
Epoch 32/100
2818/2818 ━━━━━━━━━━━━━━━━━━━━ 46s 16ms/step - accuracy: 0.4993 - loss: 2.2
203 - val_accuracy: 0.0938 - val_loss: 10.8267
Epoch 33/100
2818/2818 ━━━━━━━━━━━━━━━━━━━━ 46s 16ms/step - accuracy: 0.5047 - loss: 2.1
975 - val_accuracy: 0.0936 - val_loss: 10.9155
Epoch 34/100
2818/2818 ━━━━━━━━━━━━━━━━━━━━ 45s 16ms/step - accuracy: 0.5074 - loss: 2.1
703 - val_accuracy: 0.0889 - val_loss: 10.9875
Epoch 35/100
2818/2818 ━━━━━━━━━━━━━━━━━━━━ 46s 16ms/step - accuracy: 0.5165 - loss: 2.1
365 - val_accuracy: 0.0887 - val_loss: 11.0610
Epoch 36/100
2818/2818 ━━━━━━━━━━━━━━━━━━━━ 43s 15ms/step - accuracy: 0.5250 - loss: 2.1
037 - val_accuracy: 0.0900 - val_loss: 11.1322
Epoch 37/100
2818/2818 ━━━━━━━━━━━━━━━━━━━━ 45s 16ms/step - accuracy: 0.5277 - loss: 2.0
732 - val_accuracy: 0.0881 - val_loss: 11.1976
Epoch 38/100
2818/2818 ━━━━━━━━━━━━━━━━━━━━ 44s 16ms/step - accuracy: 0.5355 - loss: 2.0
437 - val_accuracy: 0.0921 - val_loss: 11.2664
Epoch 39/100
2818/2818 ━━━━━━━━━━━━━━━━━━━━ 46s 16ms/step - accuracy: 0.5401 - loss: 2.0
149 - val_accuracy: 0.0832 - val_loss: 11.3594
Epoch 40/100
2818/2818 ━━━━━━━━━━━━━━━━━━━━ 47s 17ms/step - accuracy: 0.5383 - loss: 2.0
114 - val_accuracy: 0.0841 - val_loss: 11.3898
Epoch 41/100
2818/2818 ━━━━━━━━━━━━━━━━━━━━ 46s 16ms/step - accuracy: 0.5493 - loss: 1.9
671 - val_accuracy: 0.0874 - val_loss: 11.4351
Epoch 42/100
2818/2818 ━━━━━━━━━━━━━━━━━━━━ 45s 16ms/step - accuracy: 0.5540 - loss: 1.9
469 - val_accuracy: 0.0853 - val_loss: 11.5371
Epoch 43/100
2818/2818 ━━━━━━━━━━━━━━━━━━━━ 43s 15ms/step - accuracy: 0.5560 - loss: 1.9
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360 - val_accuracy: 0.0815 - val_loss: 11.5896
Epoch 44/100
2818/2818 ━━━━━━━━━━━━━━━━━━━━ 45s 16ms/step - accuracy: 0.5597 - loss: 1.9
150 - val_accuracy: 0.0843 - val_loss: 11.6201
Epoch 45/100
2818/2818 ━━━━━━━━━━━━━━━━━━━━ 46s 16ms/step - accuracy: 0.5638 - loss: 1.8
990 - val_accuracy: 0.0843 - val_loss: 11.7190
Epoch 46/100
2818/2818 ━━━━━━━━━━━━━━━━━━━━ 44s 16ms/step - accuracy: 0.5684 - loss: 1.8
781 - val_accuracy: 0.0843 - val_loss: 11.7730
Epoch 47/100
2818/2818 ━━━━━━━━━━━━━━━━━━━━ 44s 16ms/step - accuracy: 0.5697 - loss: 1.8
671 - val_accuracy: 0.0868 - val_loss: 11.7948
Epoch 48/100
2818/2818 ━━━━━━━━━━━━━━━━━━━━ 44s 16ms/step - accuracy: 0.5743 - loss: 1.8
423 - val_accuracy: 0.0826 - val_loss: 11.9336
Epoch 49/100
2818/2818 ━━━━━━━━━━━━━━━━━━━━ 44s 16ms/step - accuracy: 0.5798 - loss: 1.8
237 - val_accuracy: 0.0799 - val_loss: 11.9489
Epoch 50/100
2818/2818 ━━━━━━━━━━━━━━━━━━━━ 42s 15ms/step - accuracy: 0.5772 - loss: 1.8
205 - val_accuracy: 0.0794 - val_loss: 12.0018
Epoch 51/100
2818/2818 ━━━━━━━━━━━━━━━━━━━━ 44s 16ms/step - accuracy: 0.5840 - loss: 1.7
919 - val_accuracy: 0.0788 - val_loss: 12.0259
Epoch 52/100
2818/2818 ━━━━━━━━━━━━━━━━━━━━ 45s 16ms/step - accuracy: 0.5864 - loss: 1.7
890 - val_accuracy: 0.0834 - val_loss: 12.1450
Epoch 53/100
2818/2818 ━━━━━━━━━━━━━━━━━━━━ 45s 16ms/step - accuracy: 0.5885 - loss: 1.7
719 - val_accuracy: 0.0841 - val_loss: 12.1583
Epoch 54/100
2818/2818 ━━━━━━━━━━━━━━━━━━━━ 43s 15ms/step - accuracy: 0.5951 - loss: 1.7
494 - val_accuracy: 0.0809 - val_loss: 12.1859
Epoch 55/100
2818/2818 ━━━━━━━━━━━━━━━━━━━━ 42s 15ms/step - accuracy: 0.5959 - loss: 1.7
402 - val_accuracy: 0.0790 - val_loss: 12.2468
Epoch 56/100
2818/2818 ━━━━━━━━━━━━━━━━━━━━ 42s 15ms/step - accuracy: 0.5948 - loss: 1.7
392 - val_accuracy: 0.0769 - val_loss: 12.3072
Epoch 57/100
2818/2818 ━━━━━━━━━━━━━━━━━━━━ 42s 15ms/step - accuracy: 0.5966 - loss: 1.7
289 - val_accuracy: 0.0805 - val_loss: 12.3389
Epoch 58/100
2818/2818 ━━━━━━━━━━━━━━━━━━━━ 43s 15ms/step - accuracy: 0.6027 - loss: 1.7
049 - val_accuracy: 0.0777 - val_loss: 12.3883
Epoch 59/100
2818/2818 ━━━━━━━━━━━━━━━━━━━━ 46s 16ms/step - accuracy: 0.6036 - loss: 1.6
910 - val_accuracy: 0.0782 - val_loss: 12.4821
Epoch 60/100
2818/2818 ━━━━━━━━━━━━━━━━━━━━ 46s 16ms/step - accuracy: 0.6049 - loss: 1.6
910 - val_accuracy: 0.0788 - val_loss: 12.4776
Epoch 61/100
2818/2818 ━━━━━━━━━━━━━━━━━━━━ 45s 16ms/step - accuracy: 0.6086 - loss: 1.6
807 - val_accuracy: 0.0784 - val_loss: 12.5230
Epoch 62/100
2818/2818 ━━━━━━━━━━━━━━━━━━━━ 45s 16ms/step - accuracy: 0.6121 - loss: 1.6
597 - val_accuracy: 0.0740 - val_loss: 12.5724
Epoch 63/100
2818/2818 ━━━━━━━━━━━━━━━━━━━━ 46s 16ms/step - accuracy: 0.6118 - loss: 1.6
576 - val_accuracy: 0.0750 - val_loss: 12.6212
Epoch 64/100
2818/2818 ━━━━━━━━━━━━━━━━━━━━ 46s 16ms/step - accuracy: 0.6119 - loss: 1.6
541 - val_accuracy: 0.0784 - val_loss: 12.6696
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Epoch 65/100
2818/2818 ━━━━━━━━━━━━━━━━━━━━ 46s 16ms/step - accuracy: 0.6160 - loss: 1.6
393 - val_accuracy: 0.0769 - val_loss: 12.7313
Epoch 66/100
2818/2818 ━━━━━━━━━━━━━━━━━━━━ 44s 16ms/step - accuracy: 0.6171 - loss: 1.6
284 - val_accuracy: 0.0775 - val_loss: 12.7759
Epoch 67/100
2818/2818 ━━━━━━━━━━━━━━━━━━━━ 44s 15ms/step - accuracy: 0.6179 - loss: 1.6
235 - val_accuracy: 0.0765 - val_loss: 12.7887
Epoch 68/100
2818/2818 ━━━━━━━━━━━━━━━━━━━━ 46s 16ms/step - accuracy: 0.6177 - loss: 1.6
247 - val_accuracy: 0.0733 - val_loss: 12.8602
Epoch 69/100
2818/2818 ━━━━━━━━━━━━━━━━━━━━ 45s 16ms/step - accuracy: 0.6214 - loss: 1.5
983 - val_accuracy: 0.0721 - val_loss: 12.9085
Epoch 70/100
2818/2818 ━━━━━━━━━━━━━━━━━━━━ 46s 16ms/step - accuracy: 0.6177 - loss: 1.6
033 - val_accuracy: 0.0775 - val_loss: 12.9120
Epoch 71/100
2818/2818 ━━━━━━━━━━━━━━━━━━━━ 45s 16ms/step - accuracy: 0.6255 - loss: 1.5
906 - val_accuracy: 0.0792 - val_loss: 12.9514
Epoch 72/100
2818/2818 ━━━━━━━━━━━━━━━━━━━━ 44s 16ms/step - accuracy: 0.6291 - loss: 1.5
717 - val_accuracy: 0.0767 - val_loss: 12.9828
Epoch 73/100
2818/2818 ━━━━━━━━━━━━━━━━━━━━ 47s 17ms/step - accuracy: 0.6254 - loss: 1.5
843 - val_accuracy: 0.0752 - val_loss: 13.0157
Epoch 74/100
2818/2818 ━━━━━━━━━━━━━━━━━━━━ 46s 16ms/step - accuracy: 0.6261 - loss: 1.5
813 - val_accuracy: 0.0744 - val_loss: 13.1221
Epoch 75/100
2818/2818 ━━━━━━━━━━━━━━━━━━━━ 45s 16ms/step - accuracy: 0.6282 - loss: 1.5
760 - val_accuracy: 0.0763 - val_loss: 13.0638
Epoch 76/100
2818/2818 ━━━━━━━━━━━━━━━━━━━━ 47s 17ms/step - accuracy: 0.6315 - loss: 1.5
567 - val_accuracy: 0.0786 - val_loss: 13.1609
Epoch 77/100
2818/2818 ━━━━━━━━━━━━━━━━━━━━ 46s 16ms/step - accuracy: 0.6307 - loss: 1.5
631 - val_accuracy: 0.0725 - val_loss: 13.2068
Epoch 78/100
2818/2818 ━━━━━━━━━━━━━━━━━━━━ 46s 16ms/step - accuracy: 0.6327 - loss: 1.5
482 - val_accuracy: 0.0746 - val_loss: 13.2300
Epoch 79/100
2818/2818 ━━━━━━━━━━━━━━━━━━━━ 47s 17ms/step - accuracy: 0.6324 - loss: 1.5
493 - val_accuracy: 0.0744 - val_loss: 13.2764
Epoch 80/100
2818/2818 ━━━━━━━━━━━━━━━━━━━━ 45s 16ms/step - accuracy: 0.6345 - loss: 1.5
406 - val_accuracy: 0.0725 - val_loss: 13.3152
Epoch 81/100
2818/2818 ━━━━━━━━━━━━━━━━━━━━ 46s 16ms/step - accuracy: 0.6350 - loss: 1.5
362 - val_accuracy: 0.0752 - val_loss: 13.3798
Epoch 82/100
2818/2818 ━━━━━━━━━━━━━━━━━━━━ 45s 16ms/step - accuracy: 0.6376 - loss: 1.5
281 - val_accuracy: 0.0750 - val_loss: 13.3461
Epoch 83/100
2818/2818 ━━━━━━━━━━━━━━━━━━━━ 47s 17ms/step - accuracy: 0.6372 - loss: 1.5
263 - val_accuracy: 0.0744 - val_loss: 13.4211
Epoch 84/100
2818/2818 ━━━━━━━━━━━━━━━━━━━━ 43s 15ms/step - accuracy: 0.6354 - loss: 1.5
258 - val_accuracy: 0.0769 - val_loss: 13.4062
Epoch 85/100
2818/2818 ━━━━━━━━━━━━━━━━━━━━ 43s 15ms/step - accuracy: 0.6388 - loss: 1.5
180 - val_accuracy: 0.0775 - val_loss: 13.4648
Epoch 86/100
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2818/2818 ━━━━━━━━━━━━━━━━━━━━ 41s 15ms/step - accuracy: 0.6384 - loss: 1.5
172 - val_accuracy: 0.0799 - val_loss: 13.4651
Epoch 87/100
2818/2818 ━━━━━━━━━━━━━━━━━━━━ 42s 15ms/step - accuracy: 0.6361 - loss: 1.5
182 - val_accuracy: 0.0742 - val_loss: 13.5433
Epoch 88/100
2818/2818 ━━━━━━━━━━━━━━━━━━━━ 43s 15ms/step - accuracy: 0.6382 - loss: 1.5
095 - val_accuracy: 0.0737 - val_loss: 13.6122
Epoch 89/100
2818/2818 ━━━━━━━━━━━━━━━━━━━━ 42s 15ms/step - accuracy: 0.6448 - loss: 1.4
914 - val_accuracy: 0.0752 - val_loss: 13.6058
Epoch 90/100
2818/2818 ━━━━━━━━━━━━━━━━━━━━ 41s 14ms/step - accuracy: 0.6418 - loss: 1.4
963 - val_accuracy: 0.0777 - val_loss: 13.6330
Epoch 91/100
2818/2818 ━━━━━━━━━━━━━━━━━━━━ 42s 15ms/step - accuracy: 0.6408 - loss: 1.4
928 - val_accuracy: 0.0737 - val_loss: 13.6156
Epoch 92/100
2818/2818 ━━━━━━━━━━━━━━━━━━━━ 44s 15ms/step - accuracy: 0.6457 - loss: 1.4
827 - val_accuracy: 0.0786 - val_loss: 13.6955
Epoch 93/100
2818/2818 ━━━━━━━━━━━━━━━━━━━━ 41s 15ms/step - accuracy: 0.6409 - loss: 1.4
890 - val_accuracy: 0.0712 - val_loss: 13.7012
Epoch 94/100
2818/2818 ━━━━━━━━━━━━━━━━━━━━ 42s 15ms/step - accuracy: 0.6446 - loss: 1.4
764 - val_accuracy: 0.0712 - val_loss: 13.6881
Epoch 95/100
2818/2818 ━━━━━━━━━━━━━━━━━━━━ 43s 15ms/step - accuracy: 0.6441 - loss: 1.4
767 - val_accuracy: 0.0712 - val_loss: 13.7917
Epoch 96/100
2818/2818 ━━━━━━━━━━━━━━━━━━━━ 42s 15ms/step - accuracy: 0.6472 - loss: 1.4
728 - val_accuracy: 0.0737 - val_loss: 13.7347
Epoch 97/100
2818/2818 ━━━━━━━━━━━━━━━━━━━━ 44s 15ms/step - accuracy: 0.6483 - loss: 1.4
629 - val_accuracy: 0.0759 - val_loss: 13.8328
Epoch 98/100
2818/2818 ━━━━━━━━━━━━━━━━━━━━ 44s 16ms/step - accuracy: 0.6440 - loss: 1.4
784 - val_accuracy: 0.0710 - val_loss: 13.8793
Epoch 99/100
2818/2818 ━━━━━━━━━━━━━━━━━━━━ 43s 15ms/step - accuracy: 0.6474 - loss: 1.4
528 - val_accuracy: 0.0740 - val_loss: 13.9093
Epoch 100/100
2818/2818 ━━━━━━━━━━━━━━━━━━━━ 44s 16ms/step - accuracy: 0.6494 - loss: 1.4
576 - val_accuracy: 0.0691 - val_loss: 13.9214
```

Save Model after training

In [16]:

```
# Save the model after training
model3.save('lstm_model3.h5')
print("Model saved as lstm_model3.h5")
```

```
WARNING:absl:You are saving your model as an HDF5 file via `model.save()` o
r `keras.saving.save_model(model)`. This file format is considered legacy.
We recommend using instead the native Keras format, e.g. `model.save('my_mo
del.keras')` or `keras.saving.save_model(model, 'my_model.keras')`.
Model saved as lstm_model3.h5
```

Load Saved model 3

In [17]:

```
# load saved model
from tensorflow.keras.models import load_model
```

```
loaded_model3 = load_model('lstm_model3.h5')
```

```
WARNING:absl:Compiled the loaded model, but the compiled metrics have yet t
o be built. `model.compile_metrics` will be empty until you train or evalua
te the model.
```

Save History for model 3

In [18]:

```
pickle.dump(history, open("history3.p", "wb"))
```

Load History for model 3

In [19]:

```
history3 = pickle.load(open("history3.p", "rb"))
```

In [ ]:

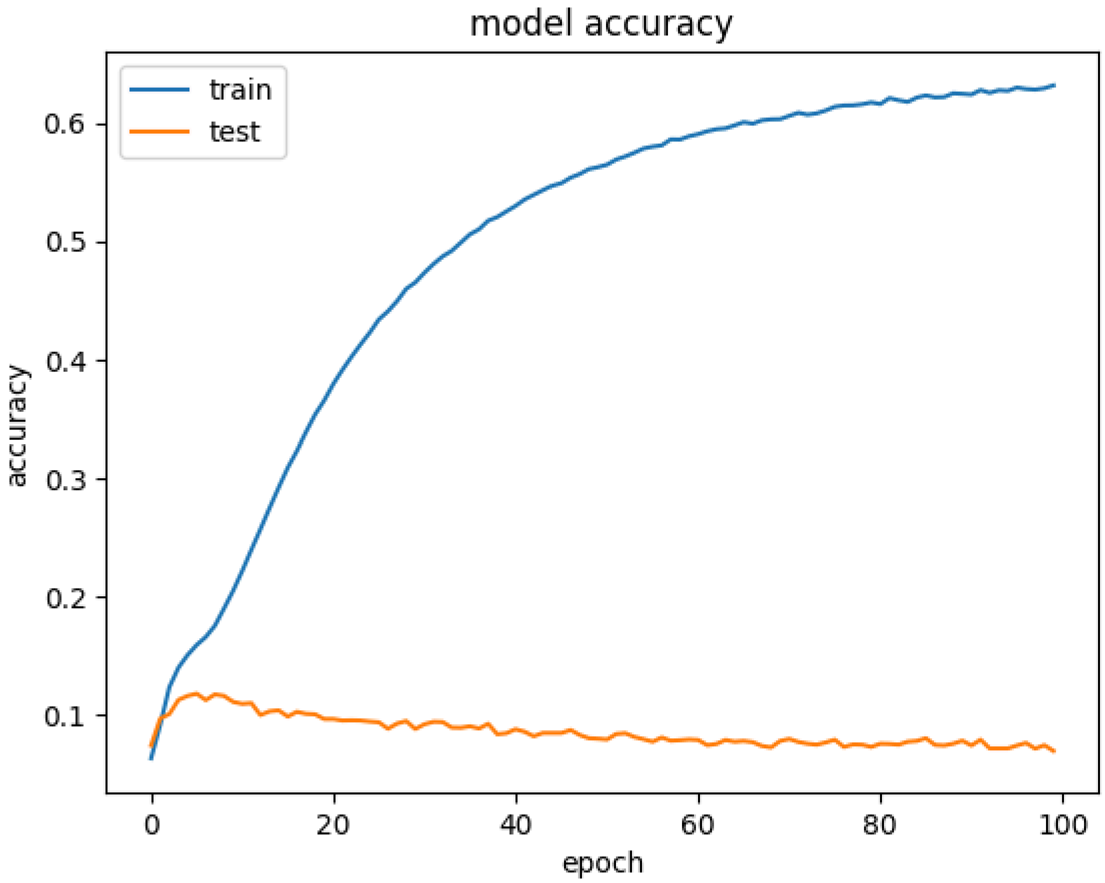
```
### Plot History - Accuracy vs Epochs  for model 3
```

In [20]:

```
plt.plot(history3['accuracy'])
plt.plot(history3['val_accuracy'])
plt.title('model accuracy')
plt.ylabel('accuracy')
plt.xlabel('epoch')
plt.legend(['train', 'test'], loc='upper left')
```

Out[20]:

```
<matplotlib.legend.Legend at 0x33c596fb0>
```



In [ ]:

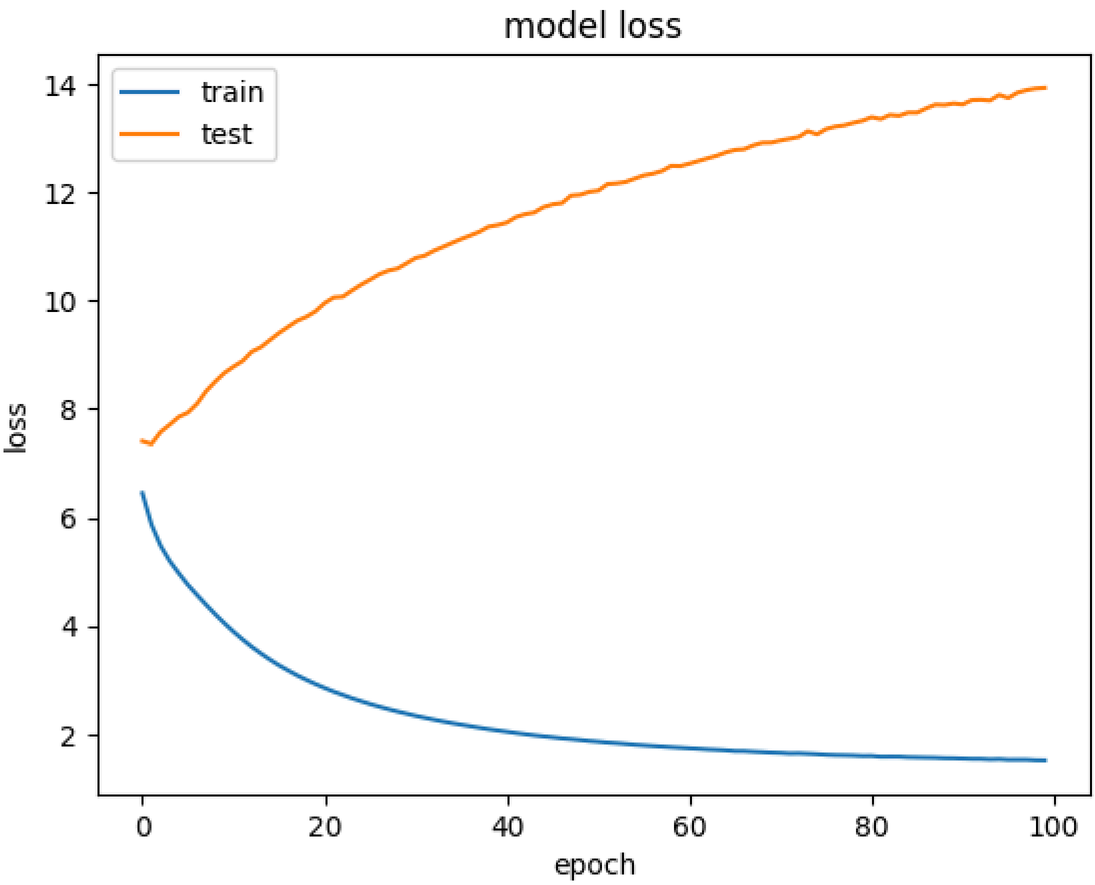
```
### Plot Loss Vs Epochs for model 3
```

In [21]:

```
plt.plot(history3['loss'])
plt.plot(history3['val_loss'])
plt.title('model loss')
plt.ylabel('loss')
plt.xlabel('epoch')
plt.legend(['train', 'test'], loc='upper left')
```

Out[21]:

```
<matplotlib.legend.Legend at 0x33c65a8c0>
```



Section 6: Predict next set of words

The code is explained below

Initial set up

- `seed_text:` This is the initial starting text (or prompt) from which the model will generate more text. In this case, it starts with "I will close the door if".
- `next_words = 5:` The variable next_words defines how many words the model will generate after the seed text. In this case, it will generate 7 new words.

For Loop for Word Prediction:

- A for loop is initiated to run next_words times (5 iterations). In each iteration, the model will predict one word and append it to seed_text.

Convert Seed Text to Tokens:

- `tokenizer.texts_to_sequences([seed_text]):` This function converts the seed_text into a sequence of integers (tokens) based on a previously fitted tokenizer.
- For example, if the tokenizer maps the word "I" to 1, "will" to 5, "close" to 9, etc., then the sentence "I will close the door if" might be converted to something like [1,

5, 9, 12, 3, 7].

- `[0]: The texts_to_sequences` method returns a list of lists, but since we are passing only one sentence, we access the first element using [0] to get the actual list of token IDs.

Pad the Sequence:

- `pad_sequences:` This function ensures that the input sequence has the same length as the expected input shape of the model. Padding is done at the beginning of the sequence (padding='pre') to match the required length.
- `max_sequence_len-1:` The length of the padded sequence is set to one less than the max_sequence_len, which is likely the length used during training. This is necessary because the model is trained to predict the next word based on a sequence of length `max_sequence_len-1` .
- The padding ensures that if the token_list is shorter than `max_sequence_len-1`, zeros are added at the start.

Model Prediction:

- `model.predict(token_list):` The padded token sequence is fed into the model, and the model predicts the next word.
- The output of model.predict will likely be a probability distribution over all possible words in the vocabulary.
- `np.argmax(..., axis=-1):` This extracts the index (token) of the word with the highest predicted probability. This index corresponds to the word that the model thinks is the most likely next word.

Find the Corresponding Word

- This loop iterates through the tokenizer's word_index dictionary, which contains the mapping of words to their corresponding token indices.
- `if index == predicted`: This checks if the token index from the word_index matches the predicted token (the one the model predicted).
- `output_word = word:` If a match is found, the corresponding word is stored in output_word. This step essentially translates the predicted token back into a human-readable word.

Update Seed Text:

- The predicted word (output_word) is appended to the original seed_text. This updated seed_text now becomes the input for the next iteration of the loop.
- After each iteration, the model will generate the next word based on the newly updated seed_text, and this process continues for next_words iterations.

In [28]:

```
# Determine a text
seed_text = "I will come"
# Predict word number
next_words = 5

for _ in range(next_words):
    # Convert seed_text to token
    token_list = tokenizer.texts_to_sequences([seed_text])[0]
    # Pad sequences to match input shape
    token_list = pad_sequences([token_list], maxlen=max_sequence_len-1, padd
    # Model prediction
    predicted = np.argmax(loaded_model3.predict(token_list), axis=-1)
    output_word = ""
    # Get the predicted word from the tokenizer's word_index
    for word, index in tokenizer.word_index.items():
        if index == predicted:
            output_word = word
            break
    # Append the predicted word to the seed text
    seed_text += " " + output_word
```

```
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 11ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 11ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 9ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 10ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 10ms/step
```

In [29]:

```
print(seed_text)
```

```
I will come to the house that i
```

End of notebook